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Detection of Pothole by Applying Convolutional Neural Network and Random Forest Techniques

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Abstract—Roads are essential for daily transportation worldwide, but their aging and usage patterns can cause deterioration of the road surface, leading to a decline in quality. This deterioration often results in the formation of potholes and cracks on the roads, which can cause damage to vehicles or pose a physical danger to occupants, particularly in underdeveloped countries. Identifying potholes in real-time can help drivers avoid them and prevent accidents. Furthermore, recording their locations and sharing them can assist other drivers and road maintenance organizations take prompt corrective measures. In our attempt to address the issue of pothole detection, we aim to combine the latest technological advancements. We aim to develop practical, reliable, adaptable, and modular solutions. To achieve this, we will compare the performance of Random Forest, a machine learning model, with CNN, a deep learning model, in detecting potholes. We will train these models using multiple datasets and analyse their performance to determine their effectiveness in pothole detection.

Keywords- Pothole Detection, Automated Detection, Random Forest, CNN

I. INTRODUCTION

The presence of potholes on roads is indeed a significant concern for both drivers and governments responsible for maintaining road infrastructure. As your statement highlights, potholes can lead to various problems, such as discomfort while driving and costly vehicle repairs. Potholes are often symptomatic of broader road maintenance issues. They can be caused or exacerbated by factors like freezing and thawing cycles, heavy traffic, and poor drainage. Addressing potholes is crucial, but fixing the underlying structural problems is equally important to prevent their recurrence. Potholes have a substantial economic impact. Repairing potholes and compensating drivers for vehicle damage represents a significant cost for governments. As you mentioned, the cost of pothole-related damage to drivers and infrastructure maintenance is substantial. Potholes pose safety risks [1-2]. They can cause accidents wildly when drivers swerve to avoid them or when they result in loss of vehicle control. Adequate road maintenance is essential to ensure the safety of road users. Pothole-related claims and compensation costs are a burden on governments and insurance companies. These costs can be reduced by proactively addressing pothole issues through proper maintenance and repair. Implementing pothole detection systems, often using technology like cameras, sensors, and artificial intelligence, can effectively address this issue. These systems can automatically identify and locate potholes, allowing authorities to prioritize repairs and respond more quickly. This can ultimately reduce the financial and safety burdens associated with potholes. While pothole detection systems can help streamline repairs, governments need to have long-term maintenance plans in place. Preventive maintenance, such as resurfacing roads before they deteriorate to forming potholes, is a cost-effective approach in the long run. Increasing public awareness about reporting potholes can also be beneficial. Citizens can help authorities identify and address potholes more effectively by saying their locations [3]. As you mentioned, the 2018 study by Cycling UK underscores the importance of maintaining road infrastructure to promote cycling as a viable and attractive mode of transportation. Better road conditions, which include addressing issues like potholes, can significantly encourage more people to choose cycling for their commutes and daily activities. As mentioned in the study, the utilization of mobile devices equipped with various sensors for pothole detection is a cost-effective and efficient approach to address road maintenance issues. Leveraging the sensor capabilities of mobile devices for pothole detection is a practical and effective approach to improving road maintenance. It takes advantage of existing technology, widespread adoption, and the ability to collect real-time data. This method can significantly contribute to safer roads, reduced repair costs, and a more efficient road maintenance process. The objective of developing an efficient and accurate system for pothole identification using image processing techniques and machine learning algorithms is commendable, as it addresses the shortcomings of existing technologies [4]. The approach outlined in the study holds promise for significantly improving road infrastructure maintenance.

II. LITERATURE SURVEY

The Author [5] focuses on pothole detection using a combination of Spectral Clustering (SC) and Deep Learning algorithms, specifically Convolutional Neural Networks (CNN) and Alex Net. Their study provides valuable insights into the effectiveness of these methods for pothole detection. The research explores two distinct approaches for pothole detection. The first approach involves Spectral Clustering and morphological operations, while the second utilizes Deep Learning algorithms, namely CNN and Alex Net. In the first approach, Spectral Clustering is applied to process input images, and morphological operations are used. A threshold classifier is then employed to detect potholes. Importantly, this method does not require any training on a large dataset. The second approach involves using Deep Learning algorithms, specifically CNN and Alex Net, for pothole detection. Deep Learning models are known for their ability to learn features from data, but they typically require a significant amount of training data.

The Author [6] focuses on pothole detection using Convolutional Neural Networks (CNN) and accelerometer data, specifically in the context of critical road infrastructure. Their study presents an innovative approach to address this issue. The research notes that the accuracy of their CNN-based pothole detection method decreased when dealing with larger datasets. This is a common challenge in machine learning, as models may become less effective when faced with abundant data due to overfitting or other factors. Researchers need to consider how their models perform at scale. The research demonstrates a novel approach to pothole detection using CNNs and accelerometer data collected through a smartphone application. Their method showed promise in accuracy, particularly when compared to existing solutions. However, they acknowledge that their approach might face challenges with larger datasets, and this is an area where further research and optimization may be needed to maintain or improve accuracy on a larger scale.

The author [7] focuses on developing a pothole detection system using the YOLOX model, a variant of the YOLO (You Only Look Once) object detection model. Their study involved training the YOLOX model for 5000 epochs and comparing its performance with other YOLO models, specifically YOLOv3 and YOLOv4. The researchers utilized the YOLOX model, designed for object detection tasks, to detect potholes. They trained the model over 5000 epochs to optimize its performance. The study compared the performance of their YOLOX-based pothole detection model with other YOLO models, including YOLOv3 and YOLOv4. The study noted a limitation in their model's performance when an image contained multiple potholes. In such cases, the model struggled to detect all potholes, resulting in a 55% identification rate for the total number of potholes in the image. This suggests a potential area for improvement, particularly in scenarios with multiple potholes. The research presents a pothole detection system based on the YOLOX model, which achieved high average precision (AP) and outperformed other YOLO models. However, there is room for improvement, particularly in cases where multiple potholes are present in a single image. Additionally, confidence threshold of 81.3% suggests that the model is relatively confident in its predictions. Further research and refinement may be needed to enhance the model's performance, especially in complex scenarios.

The study in your description explores the effectiveness of hyperparameter optimization techniques, including grid search, manual search, and randomly determined hyperparameter optimization [8]. The study compared the performance of different hyperparameter optimization techniques, namely grid search, manual search, and random search. The research found that randomly generated trials were more efficient than grid search and manual search in finding models as effective as or better. Random search is a more efficient approach in hyperparameter tuning. The research also emphasized that various hyperparameters are significant for different datasets. This observation suggests that a one-size-fits-all approach, like grid search, may not be the best choice for tuning algorithms for new datasets. Hyperparameter importance can vary; random search allows more flexibility in exploring the hyperparameter space. In summary, the author underscores the advantages of random search as an efficient method for hyperparameter optimization. It challenges the traditional belief that grid search is always suitable for low-dimensional spaces. It highlights the importance of considering dataset-specific hyperparameter significance when tuning algorithms for new datasets. This research can inform the choice of hyperparameter optimization techniques in machine learning and data analysis.

The research by the authors proposes an innovative approach for automating accurate and efficient pothole detection by integrating two-dimensional images and Ground-Penetrating Radar (GPR) data [9]. The study combines data from different sources, specifically two-dimensional images and GPR data. This integration allows for a more comprehensive and accurate analysis of pothole detection. The proposed approach was validated through a series of 50 experiments. These experiments likely involved collecting data from both image sources and GPR sensors to evaluate the performance of the pothole detection method. The results of the experiments showed impressive performance metrics, with a precision of 95.7% and a recall of 90%. High precision indicates that most identified potholes were indeed potholes, while high recall suggests that the method effectively found a significant portion of the actual potholes. In summary, the research presents a pothole detection method that combines data from various sources to achieve accurate results. The reported high precision and recall metrics indicate that the approach effectively identifies potholes, and integrating data from different sensors contributes to its success. This research offers valuable insights into improving pothole detection techniques, which can positively impact road safety and maintenance.

This paper's method and results exemplify this approach. It proposes a stereo vision-based system for detecting potholes by calculating their distance from the fitted quadratic road surface using an efficient disparity calculation algorithm [10-11]. The system provides information on pothole size, volume, and position, allowing for repair prioritization based on severity. The system achieved high accuracy in road fitting and pothole detection by setting the region of interest in front of the vehicle. The propose a real-time method for detecting potholes and assessing road conditions. Sensor data is used to classify road conditions and potholes with 93 percent, respectively, using an SVM model [12].

The author [13] has introduced a new algorithm for pothole detection to make it compatible with embedded computing environments of black box cameras. This algorithm examines numerous characteristics like length, area, variance, and trajectory to determine if candidate areas are potholes. Furthermore, the algorithm can differentiate shadows and moving vehicles from other objects. The sensitivity and precision of the algorithm reached 71% and 88%, respectively. According to an article [14], they proposed a method to detect potholes on roads using mobile sensing. They introduced a system called the Pothole Detection System that utilizes the accelerometer and GPS of an Android smartphone to identify and locate potholes quickly. Using a machine-learning approach on the “Encog” framework, the study shows that the system can detect potholes accurately by more than 95%.

The paper [115-16] introduces a new method for identifying potholes using 2D photographs, which can be used in ITS services and road network management. The authors used 2D road photos captured by a survey truck to evaluate the proposed model’s performance compared to existing techniques across different variables, such as road type, recording, and brightness. The study results are positive, and the data obtained from this model can be utilized for preventive maintenance and prompt action toward restoring and preserving the roadway. Moreover, this data can be employed to warn drivers about potential potholes on the road. This paper [17] outlines creating a mobile sensing system that utilizes a smartphone OS containing Android to collect real-time data about road irregularities. The study examines the use of participatory sensing for gathering information. Specific data processing algorithms are used for evaluation, showing a high actual positive rate of up to 90% using real-world data. Additionally, the study identifies the optimal parameters for these algorithms and provides suggestions for their application.

A study by author [18] to evaluate the effectiveness of existing pothole detection technologies. She developed a new and cost-effective system for detecting potholes and bumps on roads. The proposal uses ultrasonic sensors to detect the depth and height of potholes and humps while recording their geographical coordinates using a GPS receiver. The collected data information, such as pothole depth, bump height, and location, is stored in a cloud database, providing valuable insights for government officials and drivers. An Android application is used to inform drivers to take prudent measures to avoid accidents. The paper [19] aims to gather pothole data in various traffic conditions prevalent in India and detect them using a vision-based technique. The research assesses the effectiveness of deep learning methods regarding their detection performance and resource utilization. Through experiments on both models, the paper concludes that they offer significant advantages for pothole detection. The results have potential implications for improving road safety in India and informing similar initiatives globally. The study’s data collection and analysis methods are likely to help enhance transportation safety and infrastructure in other areas.

The researchers [20] are exploring the potential of deep learning models for pothole identification. They are deploying the working models on edge devices for real-time performance. They have chosen Raspberry Pi as the operating platform and selected various deep learning models and object recognition frameworks like YOLO and Mobile net models. To evaluate the performance of these models, they used a dataset containing images and videos of potholes in different road conditions and lighting variations. The researchers aim to identify the most suitable model for pothole detection in practical applications by testing these models on a dataset and comparing their real-time performance.

III. PROPOSED SYSTEM

Using pothole detection devices is crucial for preventing accidents and enhancing road safety. Employing multiple approaches, such as deep learning (CNN) and machine learning (Random Forest), can offer diverse methods to address this issue [21-22]. Utilizing deep knowledge and machine learning techniques allows for a broader exploration of approaches to pothole detection. Deep learning, through models like CNN, is effective at capturing complex patterns in data, while Random Forest, a traditional machine learning method, can provide interpretable results. Pothole detection methods should be subject to continuous improvement and updates. Regularly updating and retraining the models with new data can enhance their performance and accuracy. In summary, the proposed strategy that combines deep learning (CNN) and machine learning (Random Forest) for pothole detection offers a comprehensive approach to enhancing road safety. The success of such a system depends on rigorous training, performance evaluation, adaptability to different conditions, and continuous improvement to effectively prevent and mitigate accidents caused by potholes.

A. Architecture of proposed method:

The paper's focus on comparing the outcomes of pothole identification using the Random Forest model (a machine learning model) and the CNN model (a deep learning model) is a valuable approach for evaluating and selecting the best model for pothole detection. The paper's focus on comparing Random Forest and CNN models for pothole detection is a valuable

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contribution to the field. The choice between machine learning and deep learning models should be based on the application's specific requirements, the available data, and the desired trade-offs between accuracy and interpretability. The comprehensive evaluation and selection process outlined in the paper can guide the choice of the best model for pothole detection.

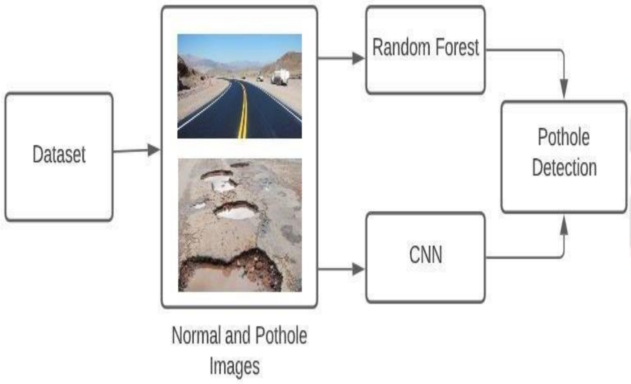


Fig 1: Flow Diagram Proposed Methodologies

Here are the key points to consider:

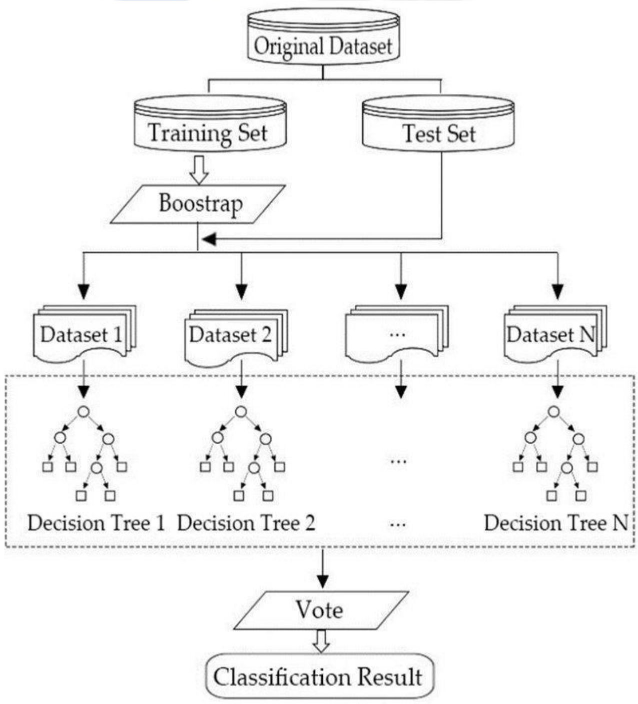
Model Comparison: Comparing the performance of different models, one from machine learning and the other from deep leaning, provides a well-rounded evaluation of pothole detection methods. Each model has strengths and limitations, and this comparison helps identify which performs better for this specific task.
Performance Metrics: The paper's emphasis on evaluating accuracy and other performance metrics is vital for assessing the models' effectiveness. In addition to accuracy, consider using metrics such as precision, recall, F1 score, and area under the receiver operating characteristic (ROC AUC) curve to get a comprehensive view of the models' performance.
Variety of Datasets: Working with various datasets is a good practice because it ensures that the selected model is robust and can handle diverse road conditions and data sources. Different datasets can simulate real-world variations and challenges.
Generalization: Evaluating the models with various datasets helps assess their generalization capabilities. A model that performs well across different datasets is more likely to be effective in real-world applications.
Hyperparameter Tuning: Don't forget to consider hyperparameter tuning for both models. Optimizing hyperparameters can significantly impact the performance of the models. Grid search, random search, or other hyperparameter optimization techniques can be used.
Validation and Cross-Validation: Proper validation and cross-validation techniques should be employed to ensure that the evaluation results are statistically sound. This helps prevent overfitting and ensures that the model's performance is reliable.
Real-world Application: Keep in mind the practicality and feasibility of deploying the selected model in real-world scenarios. Real-time performance, computational resources, and other practical considerations should be part of the evaluation.
Interpretability: Consider the interpretability of the models. While deep learning models like CNNs can be highly accurate, machine learning models like Random Forest can offer more transparency in understanding model decisions, which can be important for certain applications.
Robustness: Assess the models' robustness in terms of factors like lighting conditions, weather, and variations in road surfaces. Real-world conditions can be challenging, and the selected model should perform consistently.

B. Applying Models:

RANDOM- FOREST:

Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. It's a powerful and widely used machine learning technique known for its versatility and robustness. Random Forest is a versatile and practical machine-learning algorithm that leverages the power of ensemble learning and decision trees to make robust predictions. It is used in various applications, from classification and regression to feature selection and interpretation. Here's an overview of how Random Forest works and its architecture, as in Fig. 2.

Fig.2: Random Forest Architecture



Ensemble Learning: Random Forest is part of the ensemble learning family, which means it combines the predictions of multiple models to make more accurate and robust predictions.

Decision Trees: Each tree in a Random Forest is a decision tree, which is a simple model that makes binary decisions based on features in the data.

Bagging: Random Forest employs a technique called "bagging" (Bootstrap Aggregating) to create multiple subsets of the original dataset, each used to train a separate decision tree. This helps introduce diversity in the model.

Voting: When making predictions, each tree in the Random Forest "votes" for the class or outcome it predicts. The final

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prediction is typically the majority vote or the average prediction of all the trees.

Robustness: Random Forest is known for its robustness and resistance to overfitting, making it a popular choice for various machine learning tasks.

Versatility: It can be used for both classification and regression tasks, making it applicable to a wide range of problems.

Interpretability: While Random Forest models are not as interpretable as a single decision tree, they are still more interpretable than complex deep learning models, making them suitable for some applications.

Feature Importance: Random Forest can provide information about the importance of different features in making predictions, which is valuable for feature selection and understanding the data.

High Performance: Random Forest often achieves competitive or even state-of-the-art performance on many machine learning tasks.

C. Convolutional Neural Networks (CNNs) :

CNN is a class of deep learning algorithms designed specifically for image feature extraction and classification tasks. CNNs have revolutionized the field of computer vision and are widely used for various image-related applications. The architecture of a CNN consists of multiple layers designed to learn and extract features from images. The architecture of a CNN typically consists of several convolutional and pooling layers followed by one or more fully connected layers. The precise architecture and the number of layers can vary depending on the specific task and network design . CNNs have succeeded highly in various image-related applications, including image classification, object detection, image segmentation, and more. Their ability to automatically learn and extract hierarchical features from images has made them a cornerstone of modern computer vision. Here's an overview of the critical layers typically found in a CNN, as depicted in Figure 3. Each layer performs specific tasks, which will be described in detail below.

Input Layer: The input layer of a CNN receives the raw pixel values of an image. Images are typically represented as grids of pixel values.

Convolutional Layers: These layers are the core building blocks of a CNN. They apply convolution operations to the input image using learnable filters or kernels. These operations help the network learn spatial hierarchies of features by detecting patterns and structures in the image.

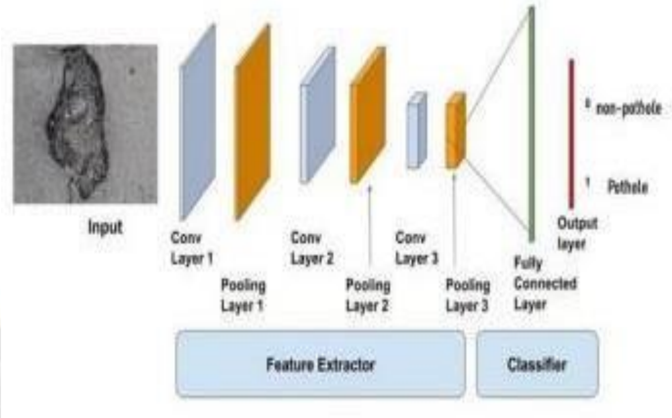

Fig.3: CNN Architecture

Input Layer: The input layer of a CNN receives the raw pixel values of an image. Images are typically represented as grids of pixel values.

Convolutional Layers: These layers are the core building blocks of a CNN. They apply convolution operations to the input image using learnable filters or kernels. These operations help the network learn spatial hierarchies of features by detecting patterns and structures in the image.

Activation Function: After each convolution operation, an activation function is applied, commonly the Rectified Linear Unit (ReLU). ReLU introduces non-linearity to the model, enabling it to learn complex patterns.

Pooling Layers: Pooling layers, such as Max-Pooling or Average-Pooling, reduce the spatial dimensions (width and height) of the feature maps while retaining the most important information. This helps reduce the number of parameters and computational complexity.

Fully Connected Layers (Dense Layers): After several convolutional and pooling layers, CNNs typically have one or more fully connected layers. These layers are similar to those in traditional neural networks and are responsible for making the final classification decision.

Flattening Layer: Before the fully connected layers, the feature maps are flattened into a one-dimensional vector. This transformation is necessary to connect the convolutional layers to the fully connected layers.

Output Layer: The output layer contains one or more neurons (nodes) representing the possible classes or categories the CNN can classify. The activation function used in the output layer depends on the task (e.g., SoftMax for multiclass classification).

Dropout Layer (Optional): To prevent overfitting, dropout layers can be added. These layers randomly drop a fraction of neurons during training to improve generalization.

SoftMax Layer (for Multiclass Classification): In the case of multiclass classification, a SoftMax layer is used to convert the network's raw output into class probabilities.

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IV. Experiment Study

A. Dataset Collection

We have collected the datasets from Kaggle and our seniors who worked previously on the same paper. To get the best accuracy and analyze which model is giving the best accuracy, a total of 5 datasets have been taken. Each dataset has subfolders named normal and potholes, and each subfolder has the images of the potholes and standard images. Of these five datasets, three are different from each other, and the other 2 are combinations of any two datasets from the three datasets.

Case 1: Here, the dataset has been taken from the Kaggle website, where the dataset has different dimensions for each image, Fig 4. and Fig 5. each subfolder had a vision of potholes and expected. In contrast, regular has 367 pictures, and pothole has 357 images.

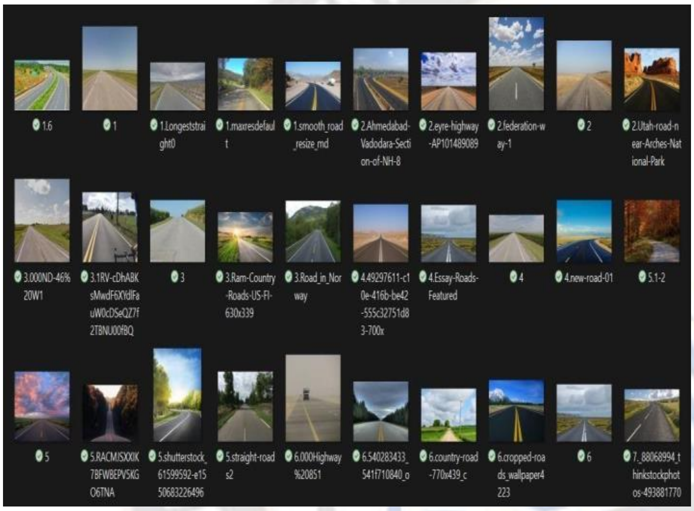
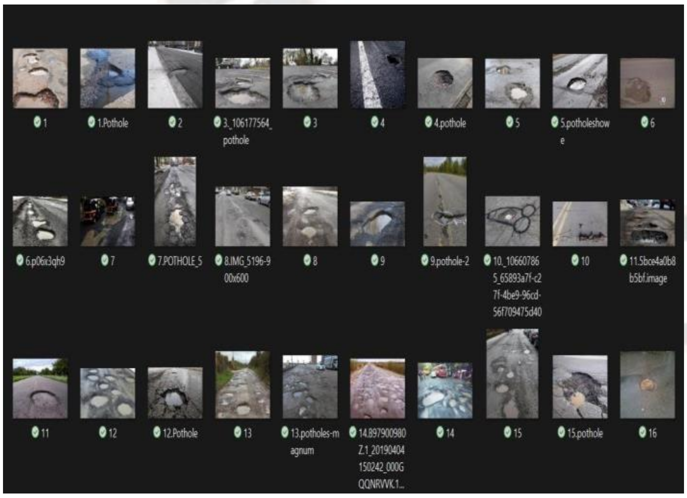


Fig 4. Normal images where each image is of different dimension.



. **Fig 5**. Pothole images where each image is of different dimension.

Case 2: This dataset has been taken from Kaggle paper where the dimensions of the pothole and typical images are 64*64 Fig 6. and Fig 7. In this dataset, specific images are 339, and pothole images are 929.

This dataset has been taken from Kaggle paper where the dimensions of the pothole and typical images are 64*64 Fig 6. and Fig 7. In this dataset, specific image.

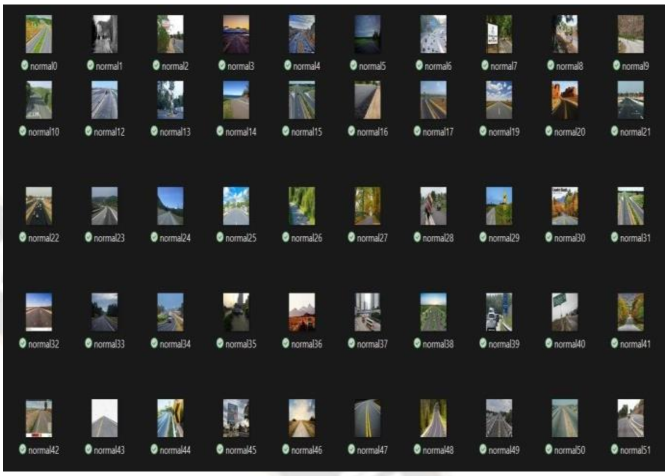


Fig 6. Normal images of dimension 64*64

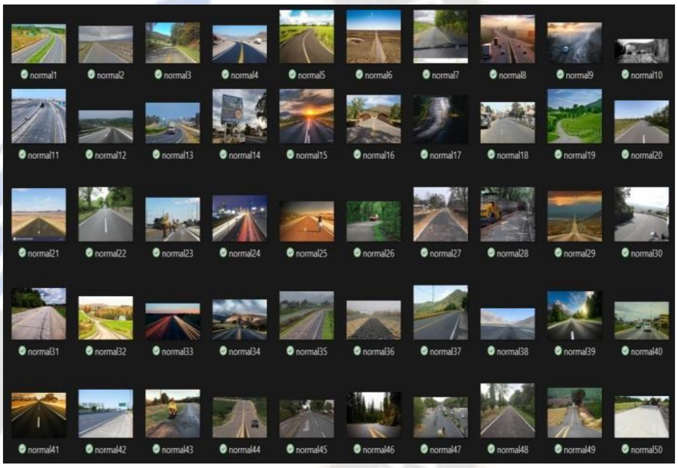


Fig 7. Pothole images of dimension 64*64

Case 3: This dataset is also taken from Kaggle where each image in this dataset consists of different dimensions Fig 8. and Fig 9. Here normal images are 351 and pothole images are 329.

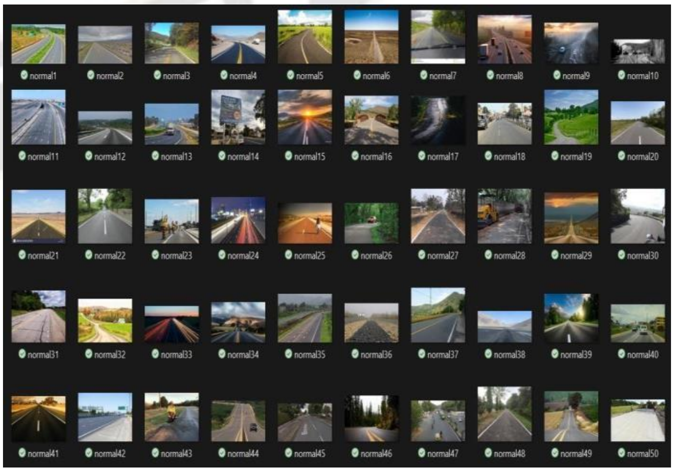


Fig 8. Normal images where each image is of different dimension.

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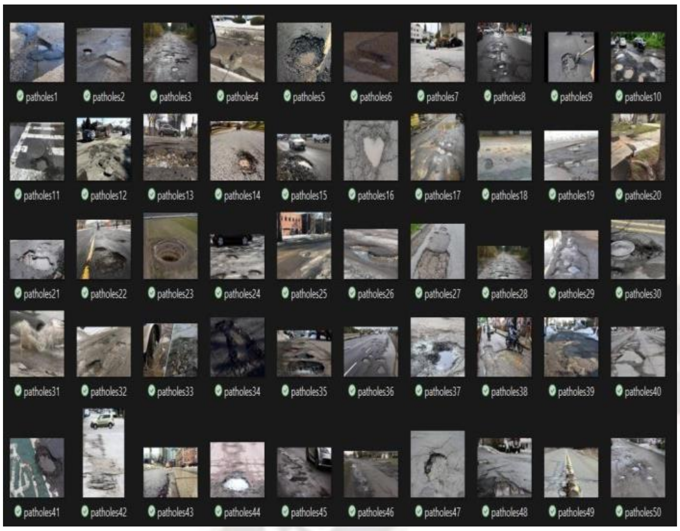

Fig 9. Pothole images where each image is of different dimension.

Case 4: This dataset is a combination of the case 1 and case 2 dataset. Here the images are combination of different dimension images and 64*64-dimension images. After combining the dataset, the normal images are 706 and pothole images are 1286.

Case 5: This dataset is a combination of case1 and case 3. Where the dataset images are only different in dimension. Here the total count of normal images is 718 and pothole images are 686.

V. Results and Discussion

We have used two models Random Forest and CNN on the multiple datasets and here are the cases for each model.

RANDOM FOREST:

Case 1: The dataset used in this study was obtained from the Kaggle website, consisting of 367 typical images and 357 pothole images. We received the highest accuracy of 80% in our observations. We noticed the performance could have been more desired due to the small dataset size. However, the results were relatively better compared to the total number of images. Additionally, we found that the accuracy decreased as we increased the test size, which can be attributed to the limited number of full images available. Despite the challenges of a small dataset, it's clear that you've made significant progress in pothole detection. Exploring these strategies and further research can improve model accuracy and robustness.

Case 2: The dataset provided by our seniors consists of 339 typical images and 929 pothole images. We achieved a maximum accuracy of 82.4% during our observations. Additionally, we noticed that altering the parameters such as estimators, random state, and test size impacted the results. Specifically, increasing the values of estimators and test size led to better outcomes. It's vital to perform hyperparameter tuning and parameter optimization to find the best combination for your dataset and task. Experimenting with different values for these parameters and analyzing their impact on model performance is a standard practice in machine learning.

Case 3: Here, typical images are 351, and pothole images are 329. We observed a maximum accuracy of 76.5%. Based on the our observations, we noticed that the accuracy varied when we changed the estimators, and this variation was also dependent on different test sizes. Experimenting with hyperparameters, including the number of estimators (estimators) and test set sizes, is essential to model development and tuning. It's common to perform hyperparameter optimization to identify the most suitable configuration for your specific dataset and task. Our observations are valuable, as they provide insights into how different factors affect model performance. Continue to fine-tune your models, analyze the impact of parameter variations, and explore additional techniques to enhance pothole detection accuracy.

Case 4: In your experiments with this combined dataset, you achieved an accuracy of 87%. This is a notable improvement compared to the previous datasets and indicates the model's ability to classify images accurately. You observed that the results varied as you changed the test size parameter. The test size parameter controls the size of the test set used for evaluation. An interesting observation was that there was an inverse relationship between test set size and accuracy, where increasing the test set size led to lower accuracy. The inverse relationship between test set size and accuracy is intriguing and may warrant further investigation. A more extensive test set generally provides a more reliable estimate of a model's generalization performance in machine learning. However, certain factors, such as data distribution or the model's sensitivity to the test set composition, could influence this relationship. This dataset with an 87% accuracy is promising, and understanding the relationship between test set size and precision can help refine the evaluation process and improve the model further.

Case 5: This dataset is created by merging case 1 and case 3 images. The combination results in a dataset with both different-sized images. The dataset includes photos with various dimensions, as well as images that were enlarged. You observed that the quality of these enlarged images may have decreased, resulting in lower accuracy than the rest of the dataset. In our observations, you achieved a high accuracy of 95%. This is a significant improvement in accuracy compared to previous datasets. The high accuracy you achieved is indeed promising. The observation regarding image quality and the potential impact on accuracy highlights the importance of image preprocessing, such as resizing and quality control, in machine learning tasks.

Case 6: The dataset is the same as in case 2, which contains images with small dimensions of 64x64 pixels. To address the issue of small image dimensions, you resized the images to 256x256 pixels. This resizing process can provide more detailed input to your machine-learning models. After resizing, you applied sharpening and cubic convolution methods to enhance image quality. Sharpening can improve images' clarity and edge definition, while cubic convolution is an interpolation technique that can improve image details. The preprocessing steps you applied, such as resizing and image enhancement techniques, have improved accuracy. Larger and more detailed images can provide more information for the models to learn from. Enhancing image quality can also lead to more accurate feature extraction and classification. It's essential to understand how preprocessing impacts model performance and to carefully

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select and apply relevant techniques to your specific dataset and task. Your approach to resizing and enhancing the dataset's images has shown positive results, and further refinements or experimentation with other preprocessing methods may lead to even better accuracy.

CNN:

Case 1: The dataset obtained from Kaggle consists of 367 typical images and 357 pothole images. Understanding your dataset and the observations made during your experiments is valuable. In your words, you achieved a high accuracy of 95%. This indicates that your models effectively correctly classified images as either normal road conditions or road sections with potholes. To address this, it's essential to carefully balance the size of the test set and the training set to ensure that the model has sufficient data for both training and evaluation. Cross-validation techniques can also help assess the model's performance on multiple test sets while using the entire dataset for training.

Case 2: The dataset provided by our seniors consists of 339 normal images and 929 pothole images. During our analysis, we achieved an accuracy of 87.8%. Interestingly, the precision remained relatively stable when we changed the test size. The variations in accuracy were minimal, indicating that the test size had a limited impact on the overall performance.

Case 3: The dataset used in this analysis was sourced from Kaggle and included 351 normal images and 329 pothole images. We achieved an accuracy of 95% during our evaluation. However, we observed that the accuracy began to decrease as we increased the test size. This decrease can be attributed to a more extensive test size reducing the amount of available training data, potentially leading to a decline in overall accuracy.

Case 4: During our analysis of this combined dataset from Case 1 and Case 2, we observed a remarkable accuracy of 97%. This result suggests that having more images in the dataset positively impacts the model's accuracy.

Case 5: This combined dataset consists of case 1 and case 2 data. During our analysis, we observed a remarkable accuracy of 99%, the highest among all the cases evaluated.

Case 6: Here, the dataset is the same as in case 2, but as the dataset images are too small to evaluate, i.e., 64*64, to increase the image size, we have resized the image properties to 256*256 and then applied the sharpening and cubic convolution methods to the resized dataset. Then, the accuracy obtained now is 87.3%.

VI. PERFORMANCE ANALYSIS BETWEEN RANDOM FOREST & CNN

The performance and resource requirements of Convolutional Neural Networks (CNN) and Random Forest is insightful. Both CNN and Random Forest have their strengths and weaknesses, and the choice of model should be influenced by factors such as available resources, the specific problem, and the desired trade-offs. we noted that CNN performs considerably more accurately than Random Forest. CNNs, especially in image-related tasks like pothole detection, are known for their ability to learn intricate features and patterns in data, which can lead to high accuracy. On the other hand, you observed that CNNs require more training time than Random Forest. Due to their architecture, CNNs are deep learning models and typically require more data and computational resources for training.

Table 1: Comparison between Random Forest and CNN

Dataset	Random Forest	CNN
Case 1	80%	95%
Case 2	82.4%	87.8%
Case 3	76.5%	95%
Case 4	87%	97%
Case 5	95%	99%
Case 6	84.2%	87.3%

Based on the performance analysis of both random forest and CNN models, it is evident that CNN yielded superior results compared to random forest. This indicates that the deep learning model CNN outperformed the machine learning model random forest. However, considering the small datasets used, it's important to note that these observations were made. The random forest may yield better results if the dataset size is increased. Currently, based on the available information, CNN is the better-performing model.

VI . CONCLUSION

In summary, it effectively encapsulates your research's main objectives and findings on pothole detection using machine learning models, specifically Random Forest and Convolutional Neural Networks (CNN). Our research contributes to the field of pothole detection by comparing two machine-learning models and shedding light on their relative performance. It underscores the importance of dataset quality and size in machine learning tasks and the potential for further advancements in the field. Your study is a step forward in improving road safety and reducing vehicle damage through automated pothole detection. The paper highlights the use of multiple datasets to evaluate the performance of these models. Using diverse datasets provides a comprehensive view of model capabilities and their adaptability to different data types. Our findings indicate that CNN outperformed Random Forest regarding speed and accuracy. CNN's ability to handle image data and complex patterns likely contributed to this superior performance. While your results are promising, you acknowledge that increasing the dataset size could further enhance the models' performance.

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